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Current Core Competencies Trend of Small to Medium Enterprises (SMEs) in China—A Concurrent Comprehensive Evaluation and Active Learning Study of Newly Listed Chinese Stocks from 2015 through 2017

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Abstract: With plenty of stocks newly listed in the Chinese stock market everyday, it becomes more and more important for managers and governess to examine the trend of core competencies for these companies. Since most companies of newly listed stocks are small to medium-sized enterprises, existing methods are not capable enough to evaluate their competitiveness. To provide an understanding for the trend of core competencies in the Chinese market, this article conducts a concurrent comprehensive evaluation and active learning methodology to analyze the newly listed stocks in SSE (Shanghai Stock Exchange Composite Index) and SZSE (Shenzhen Stock Exchange Component Index) from 2015 through 2017. There is an evidence that Number of Market Makers, Equity Financing Frequency and Executive Replacement Frequency are three main core competencies from 2015 through 2017. Authors contend that their findings in this paper question the quo of core competencies for small to medium-sized enterprises in the Chinese market.

Keywords: stock market; core competencies; comprehensive evaluation; stock data; active learning

1. Introduction

With the rapid development of Chinese economy, newly listed stocks are growing faster than ever before. In 2015, there were only about 1310 newly listed stocks in the SSE and SZSE. Meanwhile, this number came to 13,395 in 2017. This increasing trend reveals a great change among related enterprises. An interesting finding is that about 95% of these stocks belong to small or medium enterprises (SMEs).

As information technology continues to evolve, it is an urgent need to examine the trend of core competencies in the current Chinese market, relegating important issues of participation to the background. Some paper claimed that evaluation models are personable approaches. This findings offer the Chinese Governor help with publishing policies more closely aligned with demands of markets. Enterprise managers can recognize the deficiencies of their enterprises based on the evaluation results and adjust their strategies. Finally, banks and investors can select high-quality new companies based on the results of the evaluation to make more efficient investments or provide loans.

There is no existing research with quantitative comprehensive model or relevant evaluation on SMEs' capabilities. Most of the research on SMEs in SSE and SZSE are relatively qualitative research, or descriptive industry analysis. A few micro-level studies focus on the analysis of their

financing capabilities and market valuation. However, the existing evaluation methods for newly-listed SMEs are mostly based on a single evaluation index. This may lead to repeated evaluation of the company's dictation factors, while other factors lack evaluation and the model is limited in this way. A comprehensive evaluation model, which combines the existing models by giving existing models reasonable weights, seems to be an improved solution. With the help of the active learning, researchers could train an effective comprehensive SME evaluation model, with a small amount of manpower and low time cost.

From 2015 to 2017, as high-tech and innovative companies accounted for the majority of China's newly listed SMEs' stocks, the core competencies of newly-listed SMEs will be quite different from that of previous energy and concept companies. It is important for researchers, investors and SMEs to discover what are the core competencies in the current Chinese market. To give an appropriate approach to understand trends nowadays in the Chinese market, especially SMEs, this article uses comprehensive research methodology to identify the trend of core competencies in the Chinese market, processing more data than former researchers, At the same time, we mainly concentrated on the SMEs in SSE and SZSE. The following questions are what we aimed to solve:

(1) What kinds of competencies show a strong influence on the current Chinese market?
(2) What business scopes show a satisfactory development trend?
(3) What kinds of SMEs comply with a recent China market trend?

At the end of this paper, we gave an active learning based comprehensive evaluation model to carry out the training work. There are three main advantages in our proposed algorithm:

(1) Construct a comprehensive enterprise model (CEM) that included seven first-level indicators, 16 secondary-level financial indicators, and 29 second-level non-financial indicators with neither absence of important company evaluation factors nor repeated effects of responding to certain aspects of the company's competencies.
(2) Active learning was introduced in the weight assignment stage for factors to construct CEM, with less manpower cost and lower time complexity.
(3) The construction frame work of CEM in this article could be extended by introducing other evaluation models through a similar active learning method. In addition, the CEM built in this article could be implemented to different stock markets to discover the core competencies of CEMs there.

We believe that the discovering in this paper will give an accurate description of the current Chinese market to some extent, especially in SMEs' core competencies.

2. Literature Review

2.1. Company's Competencies Identification and Core Competencies Selection

This article mainly researches the trend of the companies' core competencies in the Chinese stock market. How to define and select the core competitiveness is the key to this study. In the existing research, when defining the core competencies, the researchers often only focused on one aspect among the innovation ability, growth ability, core competitiveness or certain factor in the external environment [1]. Arnold [2] divided the company's technological innovation capabilities into six components and 28 indicators based on the perspective of innovation factors. Torkkeli [3] constructed a competency model that divided the competencies in the innovation process into core competencies and system competencies for further selection work based on the perspective of the innovation process. Based on Torkkeli's work, Osagie [4] regarded the enterprise as a collection of resources and divided the company's core competencies into four parts: resources, capabilities, environment and external competitiveness. This identification system has a total of 50 specific competencies' indicators.

When it comes to the core competencies selection stage, Ljubic [5] suggested that researchers should focus on quantitative indicators and use a three-year average annual profit rate, three-year total asset turnover rate and three-year average annual asset flow ratio to conduct a quantitative evaluation on the US market's corporate competitiveness. Al-Daihani et al. [6] proposed the concept of a strategic index to specifically assess the growth of the company. Mohammed [7] demonstrated a systematic selection model which selected core competences from eight dimensions: political environment, economic environment, legal environment, financing environment and so on. Borodai [8] improved Mohammed's model by optimizing the ratio of political and environmental factors.

In the above research, there are following deficiencies in the identification and selection process of core competencies: firstly, existing research mainly focused on the competitiveness of a certain point of view, lacking of a comprehensive analysis on the company's competitiveness; secondly, when determining the core competency indicators, most of the competencies were qualitatively analyzed and lacked quantitative indicators. Finally, this research often over-relied on financial indicators and lacked non-financial core competitiveness indicators or industry-specific attribute indicators.

2.2. Evaluation Methodology in Current Stock Market Research

In the evaluation of the stock market, a large number of scholars used a single assessment method. Wei [9] deployed an improved fuzzy cognitive map model to evaluate the hotel business automatically. Yilmaz [10] and Fredriksson [11] used the multi-level gray evaluation method to evaluate the competitiveness of enterprises. Govindan [12] applied the analytic hierarchy process (AHP) to supply chain management evaluation. Xu et al. [13] improved Govindan's model in an intuition approach. Data envelopment analysis (DEA) was also a common method in stock market evaluation [14,15]. Javidi [16] proved that a rough set method is a satisfactory alternative in company evaluation. Recently, an evaluation method based on a neural network [17,18] gradually became common in some comprehensive evaluation and forecast studies. The disadvantage of these singular evaluation methods is that each method has a different focus and all methods have certain drawbacks. Due to the inconsistent research directions of these methods, the inconsistency of the evaluation results are caused.

In order to solve the problem of inconsistent evaluation results caused by a singular evaluation method, some scholars used comprehensive evaluation methods to evaluate companies in the stock market recent years. Geva [19] demonstrated a comprehensive evaluation model incorporating both market data and textual news. Yu et al. [20] carried out a further work based on Geva's findings. Patel [21] introduced a fusion of machine learning techniques into Geva's experiment, which proved to be more efficient. Shi et al. [22] combined cognitive evaluation with comprehensive evaluation in his research.

However, the existing comprehensive evaluation methods still have some problems. For example, most evaluation models lack a test of the validity and correctness for the results. At the same time, in the combination process of singular evaluation methods, there is a lack of testing of the relevance and consistency of each method, which means that the rationality of the comprehensive evaluation model itself has not been verified. Finally, the existing comprehensive evaluation models often only analyzed a limited number (around 50 to 70) of companies in a region, so that the applicability of the evaluation model is not satisfactory.

2.3. Related Works on SSE or SZSE Markets

As a new concept and cluster, SMEs in China's stock market currently have relatively little research existing in academia. Most of the existing research could be divided into two categories: one is to predict the trend of such stocks, and the other is to perform qualitative analysis on SMEs.

The trend of the stock market generally reflects the overall market trend and can be used as a reference for core competencies. Bao [23] introduced a model using fuzzy support vector machines regression in SSE. Wen [24] used a similar method in SZSE on the fractal and chaotic features.

Qiu et al. [25] gave an improved version upon Bao's model, combining C-fuzzy decision trees with time series information. Dong [26] researched the Chinese stock market's reaction to emotional valence.

Some quality analysis on SMEs partly revealed some features of core competencies of SMEs in the Chinese stock market, including functions, market positioning, and related institutional arrangements. Sedding [27] found that operations and efficiency are two initial core competencies for the Chinese stock exchange market. Chen [28] analyzed the liquidity risk of the SME stock market after the expansion from the perspective of research on transactions and trading rules. Xiaofeng [29] identified CEO Power, Information Disclosure Quality and Corporate Performance Variability are three main core competencies in SZSE stock market, with the support of the DEA model.

Among the related works on SSE and SZSE markets, we have found that there has been no research on quantitatively and comprehensively modeling and evaluating the competencies of SMEs in the Chinese stock market. In current research on core competencies of SMEs, when establishing a competencies index system, most of them only have qualitative analysis and a lack of quantitative analysis. This has also led to the repeated evaluation of certain indicators of companies, while other indicators have not taken into account during the evaluation process. This reduced the accuracy of the evaluation model.

3. Method

3.1. Construction of Competencies System

Based on Xiaofeng's quality analysis indicators [29], we combined financial data and non-financial data to sort the competencies of SMEs in the Chinese market into seven categories: Growth, Competitiveness, Financing, Teamwork, Public Opinion, External Competency and Innovation. As is shown in Figure 1, there are seven first-level competencies and 45 second-level competencies in the competencies system, including 29 non-financial competencies and 16 financial competencies. The following part will explain these competencies' indicators one by one.

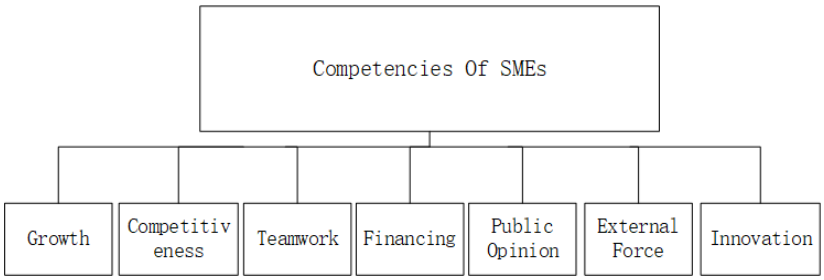

Figure 1. Overview of competencies.

Among these competencies, the company's development capacity is measured by a three-year main business compound growth rate, three-year net profit compound growth rate, three-year total assets compound growth rate and three-year capital compound growth rate. Profitability is measured by Main business income, Net profit, OPE, Return on total assets and Return on net assets. Enterprise size is measured by the two indicators of Shared capital and total assets.

Growth. The growth competency reflects the current profitability and potential profitability expectations of certain companies. The growth competency contains 11 indicators. Specific indicators and calculation methods are shown in Table 1.

Table 1. Growth competencies.

First-Level Competencies	Second-Level Competencies	Calculation Method
Growth	Three-year Main Business Compound Growth Rate	$(\sqrt{\frac{2017MainBusinessIncome}{2015MainBusinessIncome}} - 1) \times 100\%$
	Three-year Net Profit Compound Growth Rate	$(\sqrt{\frac{2017NetProfit}{2015NetProfit}} - 1) \times 100\%$
	Three-year Total Assets Compound Growth Rate	$(\sqrt{\frac{2017TotalAssets}{2015TotalAssets}} - 1) \times 100\%$
	Three-year Capital Compound Growth Rate	$(\sqrt{\frac{2017Capital}{2015Capital}} - 1) \times 100\%$
	Main Business Income	Basic Income Generated by the Company's Main Business
	Net Profit	Enterprise's After-tax Profit
	Operation Profit of Entirety (OPE)	$\frac{ProfitFromPrincipalOperations}{MainBusinessIncome} \times 100\%$
	Return on Total Assets	$\frac{NetProfit}{TotalAssets} \times 100\%$
	Return on Net Assets	$\frac{NetProfit}{NetAssets} \times 100\%$
	Share Capital	Pre-IPO Shares and Newly Issued Shares
	Total Assets	All Assets Owned by the Company that can Produce Economic Benefits

Competitiveness. The competitiveness reflects the operational capabilities, market share, and competitiveness of the company's products. Specific indicators and calculation methods are shown in Table 2.

Table 2. Competitiveness competencies.

First-Level Competencies	Second-Level Competencies	Calculation Method
Competitiveness	Account Receivable Turnover Rate	$\frac{CurrentSalesNetIncome}{(BeginningReceivables+EndReceivables)/2} \times 100\%$
	Total Asset Turnover	$\frac{NetOperatingIncome}{AverageTotalAssets} \times 100\%$
	Current Ratio	$\frac{CurrentAssets}{CurrentDebts} \times 100\%$
	User Market Share	$\frac{OperatingIncome}{TotalMarketSize} \times 100\%$
	Search Engine Index	The Value of Enterprise User Attention and Media Attention from Search Engine
	Webmaster Ranking	Longest Average Ranking of Corporate Websites
	Baidu Records	Company Related Information was Included in Baidu Database

Business capability is measured by Account receivable turnover rate and Total asset turnover. Debt paying ability is measured by Current ratio. Market share competency is measured by the remaining second-level competencies.

Teamwork. Teamwork competency reveals the organizational structure of the team and the competency of the core team. There are seven indicators in teamwork competency, indicator description and calculation methods are shown in Table 3.

Table 3. Teamwork competencies.

First-Level Competencies	Second-Level Competencies	Calculation Method
Teamwork	Number of Employees	The Number of Employees in the Company
	Graduate Index	$STD(\frac{GraduateNumber}{Numberofemployees}) \times GraduateNumber, STD(x) = \frac{x-min(x)}{max(x)-mean(x)}$
	Undergraduate Ratio	$STD(\frac{UndergraduateNumber}{NumberofEmployees}) \times UndergraduateNumber$
	Junior College Ratio	$STD(\frac{JuniorCollegeNumber}{NumberofEmployees}) \times JuniorCollegeNumber$
	Below-junior College Ratio	$STD(\frac{Below-juniorCollegeNumber}{NumberofEmployees}) \times Below-juniorCollegeNumber$
	Executive Replacements Frequency	Frequency of Replacement of Executive of the Company
	Number of Executive Replacements	Number of Replacement of Executive of the Company

Notes: Here executive includes directors, senior management personnel and supervisors of the company.

Financing. Financing competency reflects the corporate financing capabilities and current valuation, it contains eight sub-competencies, as is shown in Table 4.

Table 4. Financing competencies.

First-Level Competencies	Second-Level Competencies	Calculation Method
Financing	Number of Shareholders	The Number of Shareholders of the Company
	Business Valuation	$SharePrice \times TotalStocks$
	Shareholders' Equity	Corporate Net Assets
	Market Number of Businesses	Market Number of Businesses
	Investor's Number	The Number of Investment Companies
	Equity Financing Frequency	Equity Financing Times/Business Time
	Bond Financing Amount	The Total Amount of Corporate Bond Financing
	Total Financing Amount	Total Financing Amount of the Company

Corporate financing capacity is measured by Number of shareholders, Business valuation, Shareholders' equity, Market number of businesses and Investor's number. Business valuation is determined by the rest of second-level competencies.

Public Opinion. Public Opinion reflects the company's exposure and influence in traditional media, WeChat and Weibo. Public Opinion competencies cover the Media attention index, Weibo attention index and Wechat attention index, as is shown in Table 5.

Table 5. Public opinion competencies.

First-Level Competencies	Second-Level Competencies	Calculation Method
Public Opinion	Media Attention Index	Appearance Times in Baidu News Channel in the Past 30 Days
	Weibo Attention Index	Tweets Viewed Times in the Past 30 Days
	Wechat Attention Index	The Average Wechat Heat of the Company in the Past 30 Days

External Competency. External Competency includes Popularity of industry and Regional level of the location, which indicates the popularity of the industry the company belongs to and the competitiveness of the located region, as in Table 6.

Table 6. External competencies.

First-Level Competencies	Second-Level Competencies	Calculation Method
External Competency	Popularity of Industry	The Popularity of the Industry the Company Belongs to
	Regional Level of the Location	The Level of Area Where the Company's Main Office is Located

Innovation. Innovation competency shows an enterprise's intangible assets' transformation ability and development ability, and specifics are shown in Table 7.

Table 7. Innovation competencies.

First-Level Competencies	Second-Level Competencies	Calculation Method
Innovation Competency	The Number of Invention Patents	The Number of Invention Patents Owned by the Company
	Computer Copyright Quantity	The Number of Registered Computer Copyrights owned by the Company
	Total Number of Certificates	The Total Number of Corporate-owned Certificates
	Total Number of Trademarks	Total Number of Registered Trademarks
	Research and Development (R&D) Personnel Proportion of Employees	$\frac{Number of R\&Ds}{Number of Employees} \times 100\%$
	Number of Subsidiaries	Number of Subsidiaries of the Company
	Percentage of R&D Investment to Operating Revenue	$\frac{R\&D Investments}{Total Operating Revenue} \times 100\%$

3.2. Data Selection and Data Preprocessing

According to the above competencies index system, we have selected the data of 3430 SMEs newly listed in the last three years (2015–2017) from SSE and SZSE. The data acquisition process is shown in the chart below, as in Figure 2.

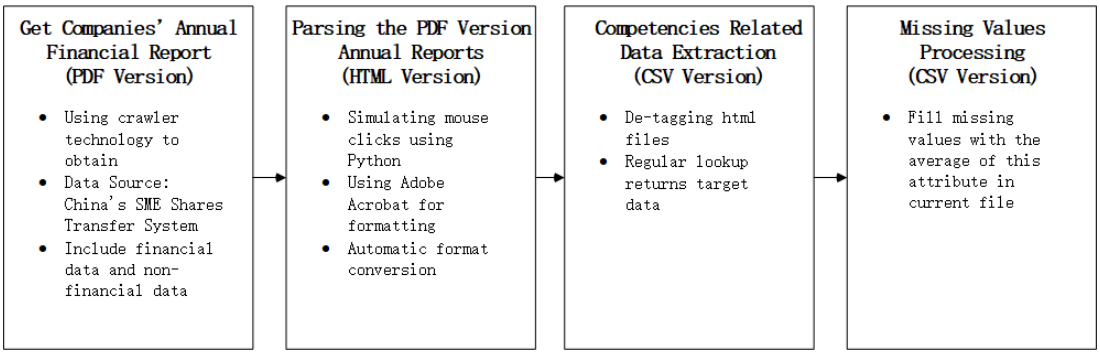

Figure 2. Overview of data acquisition and data preprocessing.

Since all SMEs in China must publish complete annual report information in the National Equities Exchange and Quotations (NEEQ) system every year, we used crawlers to obtain annual data of 3430 target SMEs from 2015 to 2017 from NEEQ. The crawler works as shown in Figure 3.

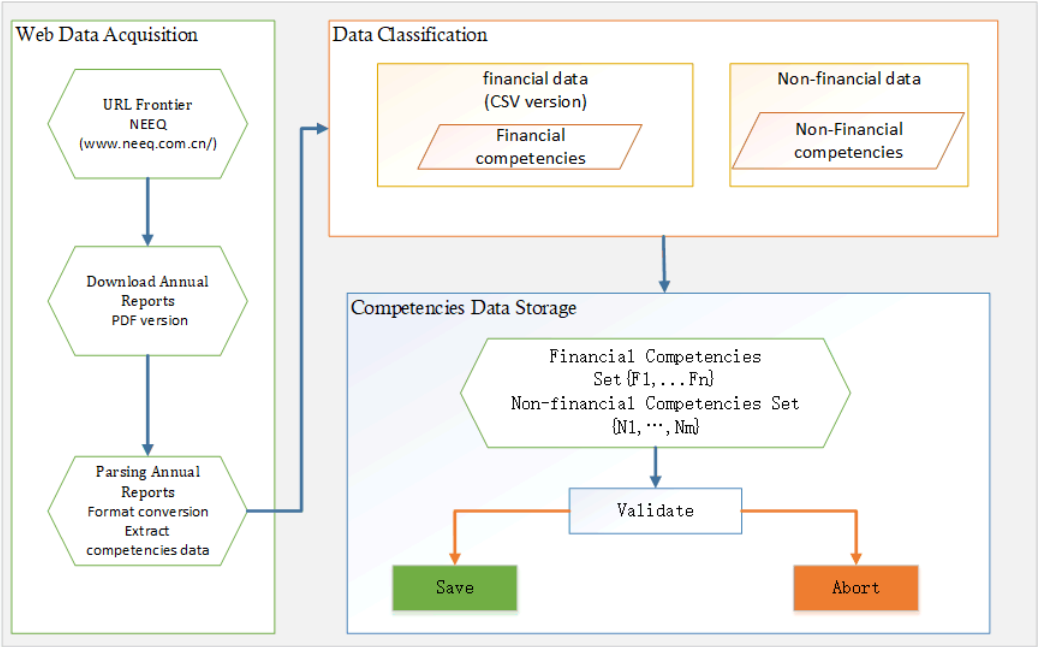

Figure 3. Structure of crawler in this paper.

Since the company's annual reports published in NEEQ are documents all in PDF versions, which makes it difficult to extract financial and non-financial data. We firstly converted the PDF version annual report to HTML format, and then use regular expressions to extract the target competencies data from the HTML file.

In the end, there are 154,350 records; among them, 3125 records are missing values (2%). After going through the CEMs' own websites, asking the CEM directly or collecting information from daily news, we fill 2703 missing values with correct values. For the left part of missing values (422, 0.27%), since there is no data loss for two consecutive years, we fill in the corresponding data of the CEM in the previous year or the next year so that there are no missing values for all records.

The left part of Figure 4 shows an example of an annual report in the NEEQ system. All annual reports are divided into chapters, each of which contains our defined competencies indicators. After preprocessing, the unstructured competencies data originally in the PDF annual report will be formatted to the structured CSV data shown in the right part of Figure 4.

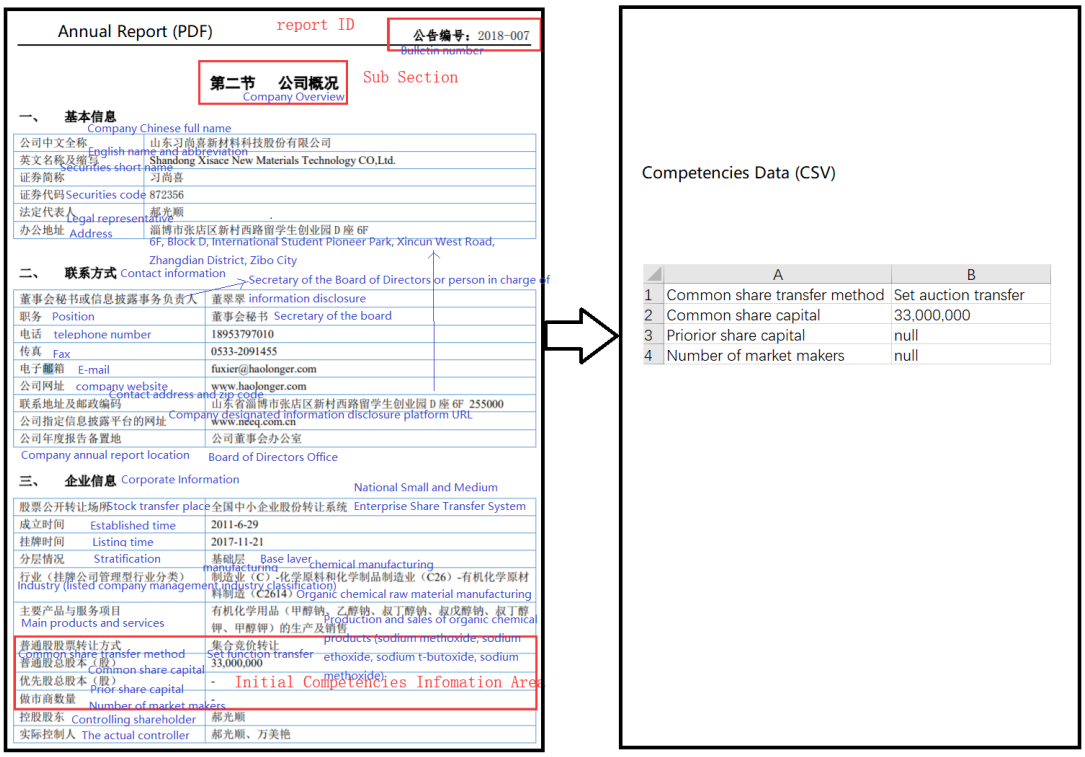

Figure 4. An example of an initial annual report and competencies data after preprocessing. (Blue text for translation).

3.3. Comprehensive Evaluation Model

As SMEs entered the market, their profitability and net profit rate in a certain period largely reflect the competitiveness of the company in the current market. In this section, we hope to propose a comprehensive evaluation model (CEM), which ultimately ranks the competitiveness of the enterprise as closely as possible to the net profit margin of the SMEs within a certain period of time. In this way, through the weights of the various competencies indicators in the model, we can know which competencies are the core competencies (which greatly affected the competitiveness of an SME) for SMEs in the current Chinese market, and, at the same time, we can discover some common characteristics of SMEs with high scores under this CEM. The construction framework of CEM is shown in Figure 5.

In this article, we applied AHP, entropy and the CRITIC (Criteria Importance Though Intercrieria Correlation) method to the same hierarchical structure (as in Figure 1 and Tables 1–7). All of the three methods above were applied to calculate the weight of the second layer of competencies (45 sub-competencies, see in Tables 1–7). As shown in Figure 6, we want to obtain a generalized linear function Figure 6b, in which $x_i, (i = 1, 2, \cdots, 45)$ represents the specific value of each sub-competency, $w_i, (i = 1, 2, \cdots, 45)$ represents the competitive weight in the generalized linear function, and the final *competency* represents the comprehensive competency of a certain SME. For each of the method (AHP, Entropy and CRITIC), we calculate the weights of the generalized linear functions corresponding to them, and obtain the weight vectors W_1 (as in Formula (2)), W_2 (as in Formula (4)) and W_3 (as in Formula (9)). The fused generalized linear function whose weight vector W is obtained by linear combination of the three weight vectors (as in Formula (11)), and the weight c_i of each vector will be adjusted by the active learning process (as in Algorithm 1).

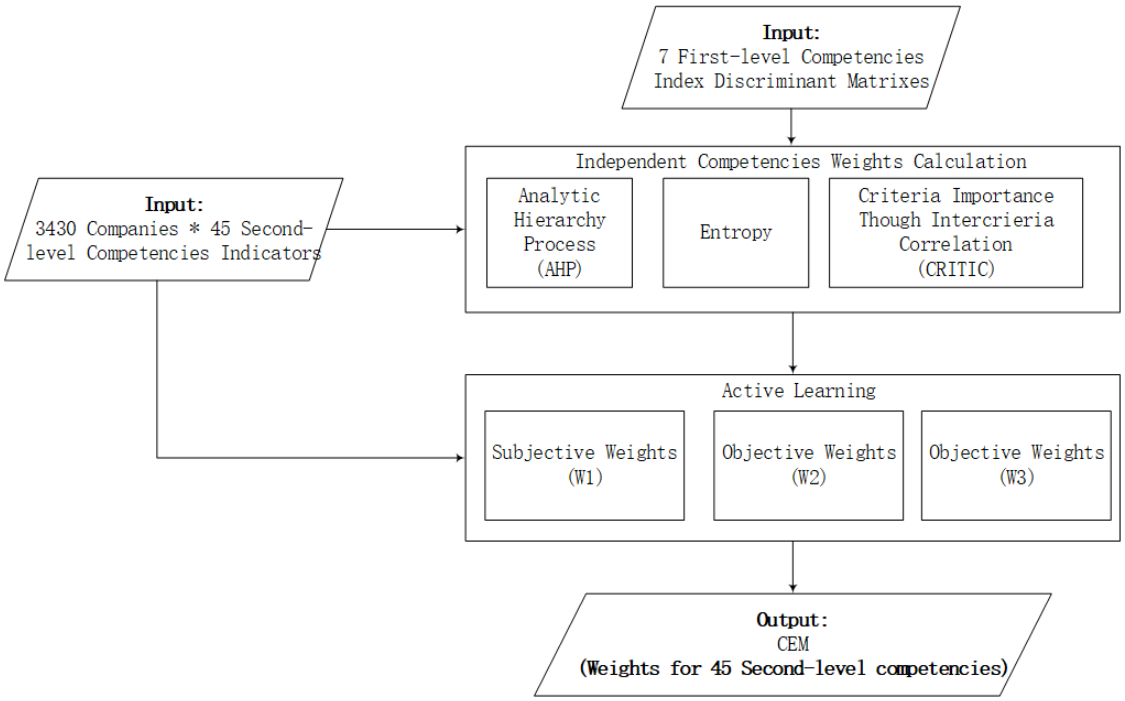

Figure 5. Framework of CEM for competencies of SMEs in China.

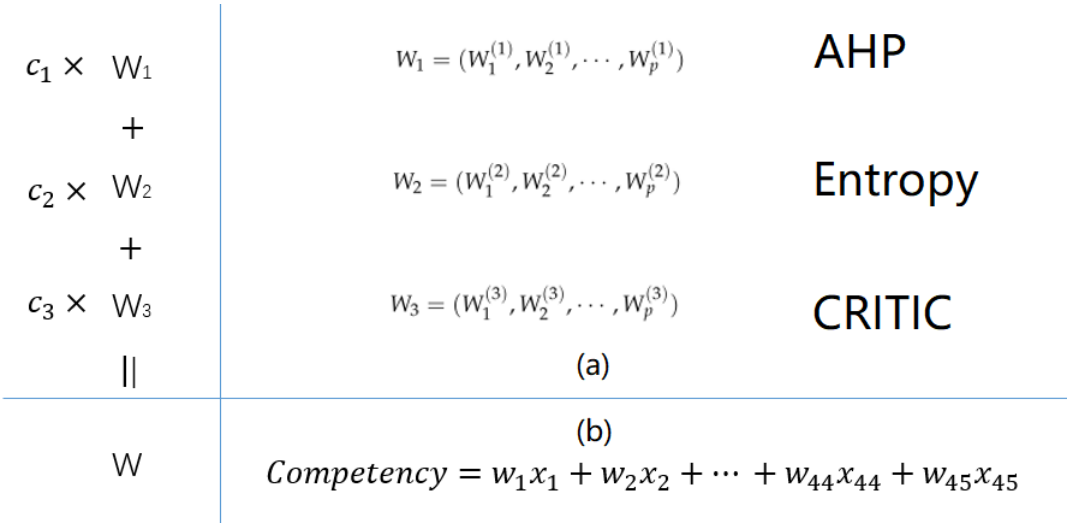

Figure 6. Framework of CEM for Competencies of SMEs in China.

Once we calculate the corresponding weights through AHP, Entropy or CRITIC, we obtain the corresponding generalized linear function, which can calculate the comprehensive competency of an SME under the corresponding method. Here, we calculated the comprehensive competency of 3430 SMEs by the generalized linear functions of AHP, Entropy and CRITIC. It should be noted that each competitiveness index has been normalized, and its value is between 0 and 1, so we set a threshold of 0.5 and SME with comprehensive competency greater than 0.5 is considered to be highly competitive, an SME with a competency less than 0.5 is considered to be weakly competitive. Therefore, 3430 SMEs were divided into two categories. At this time, we will refer to the actual situation of the market value of the corresponding SMEs (the top 50% of the market capitalization of 3430 SMEs were regarded as strong competitiveness, and the latter 50% were regarded as having weaker competitiveness), calculating the accuracy and error rate of the competitive calculation function of the AHP, Entropy and

CRITIC methods. Finally, the performance of CEM obtained through active learning will be compared with the performances of these three methods.

AHP. Analytic Hierarchy Process (AHP) is an effective method of operations research. It has a complete set of processing methods and processes for analyzing and quantifying simultaneous problems, which can introduce people's judgment and related experiences into the system and quantify them, having a scientific way of thinking. AHP's main features are: when analyzing problems with hierarchical structures, the problem is broken down into multiple single-layer problems, and finally a comprehensive evaluation is performed; emphasis is placed on the contrast of different factors, and weights are often used to make it impractical ranging from level 1 to 9.

We firstly established a three-tiered structure through AHP. The AHP structure we use here is shown as in Figure 1. Detailed information of sub-criteria are illustrated in Tables 1–7. The target layer is the comprehensive development capability of the enterprise, the criteria layer is the first-level competencies layer, and the sub-criterion layer is the second-level competencies layer; then, the questionnaires are designed and the experts were asked to adopt the 1 to 9 scale method to construct the judgment matrix between each layer of factors, then calculating competencies' weights.

The expert team consists of 18 people in the following three types: six CEM executives, long-term responsible for CEM market business, familiar with current market conditions; six financial professors from Tsinghua University and Peking University, who maintain long-term research in CEM field and six managers of the NEEQ website, the main indicators of NEEQ are set by them. Since the expert team includes researchers with rich research experience, business operators with a lot of market experience and designers of NEEQ systems, we can think that the scores of the expert teams are authoritative.

The weight vector of the criterion layer (first-level competencies layer, seven competencies) obtained by the AHP method is:

$$W_0 = (W_1^{(0)}, W_2^{(0)}, \cdots, W_7^{(0)}). \tag{1}$$

The weight vector of the sub-criterion layer (second-level competencies layer, 45 sub-competencies) obtained by the AHP method is:

$$W_1 = (W_1^{(1)}, W_2^{(1)}, \cdots, W_{45}^{(1)}). \tag{2}$$

Entropy. The entropy value is a thermodynamic concept used to measure the disorder of the system. The principle of the entropy method is that, if the index's entropy value is smaller, the more information the indicator provides, the higher the weight in the evaluation. The specific calculation method is as follows:

The weight of the ith sample in the jth indicator is:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}. \tag{3}$$

The entropy of the jth indicator is:

$$e_j = -k \sum_{i=1}^{n} p_{ij} ln(p_{ij}), k = \frac{1}{ln(n)} > 0, e_j > 0. \tag{4}$$

The difference coefficient of index x_j is:

$$g_j = 1 - e_j. \tag{5}$$

The weight of the jth indicator is:

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j}, j = 1, 2, 3 \cdots, m. \tag{6}$$

Similarly, the entropy method is applied to calculate the weights vector of the second-level competencies (second-level competencies layer, 45 sub-competencies) relative to the target layer, which is expressed as:

$$W_2 = (W_1^{(2)}, W_2^{(2)}, \cdots, W_{45}^{(2)}). \tag{7}$$

CRITIC. The CRITIC method (the importance of Criteria is related to Intercrieria) is an objective weighting method. When calculating index weights, two factors are considered. One is the contrast intensity, also the conflict, which refers to the size of the difference between each data in a certain index column. The difference is shown by the standard deviation. The larger the contrast intensity is, the greater the weight of the corresponding indicator is; the correlation between the indicators is also a consideration factor. If the correlation between a certain indicator and other indicators is relatively large, it means that part of the information expressed by this indicator can be replaced by other indicators. The weight of such indicator should be small. The CRITIC method is calculated as follows:

$$w_j = \frac{C_j}{\sum_{j=1}^{m} C_j}, j = 1, 2, 3 \cdots, m \; C_j = \sigma \sum_{k=1}^{m}; C_{1-r_{kj}}, j = 1, 2, \cdots, m. \tag{8}$$

In Equation (8), r_{kj} refers to the correlation coefficient between index k and index j. σ_j represents for the standard deviation of index j:

$$W_3 = (W_1^{(3)}, W_2^{(3)}, \cdots, W_{45}^{(3)}). \tag{9}$$

The CRITIC method calculates the weight vector of the second-level competencies (second-level competencies layer, 45 sub-competencies) relative to the target layer.

The advantage of the AHP algorithm is that it considers the opinions of experts on the importance of competencies. The disadvantage is that they sometimes result in subjective misjudgments.

Disturbance and objectively empowering methods (Entropy and CRITIC), rely entirely on objective data and lack understanding of practical issues.

Therefore, in order to overcome the shortcomings of the two methods of weighting, to exert their respective advantages, the solution is required to obtain the optimal combination of the two methods of weighting.

3.4. Active Learning and Evaluating

We finally hope to get a classifier similar to the following Formula (10):

$$H_x = \begin{bmatrix} A_1 & \cdots & A_{45} \end{bmatrix} \times \begin{bmatrix} x_1 \\ \cdots \\ x_{45} \end{bmatrix}. \tag{10}$$

Through this classifier, the scores of various competency indicators of SMEs ($x_1, x_2, \cdots, x_{45}$) are taken as input, and finally the competitiveness score of the enterprise H_x is obtained. In Formula (10), the value of A is given by the following Formula (11):

$$A = c_1 W_1 + c_2 W_2 + c_3 W_3. \tag{11}$$

When the value of H_x is greater than a certain threshold V, it can be considered that the enterprise has strong competitiveness. On the contrary, the enterprise is considered to have weaker competitiveness. In this way, the CEM can be based on the weight of subjective factors and the weight of objective factors comprehensively determine the competitiveness of the company. In the traditional evaluation model, there is no comprehensive weight calculation process. A simple synthesis idea is to use a large amount of annotation data to train the CEM. However, this requires a lot of manual annotation and is very time consuming.

Here, we have introduced active learning to combine the various subjective weights and objective weights. Active learning requires only a small number of manual annotations with very few rounds, with a good enough training result obtained. The process of active learning is shown in Figure 7.

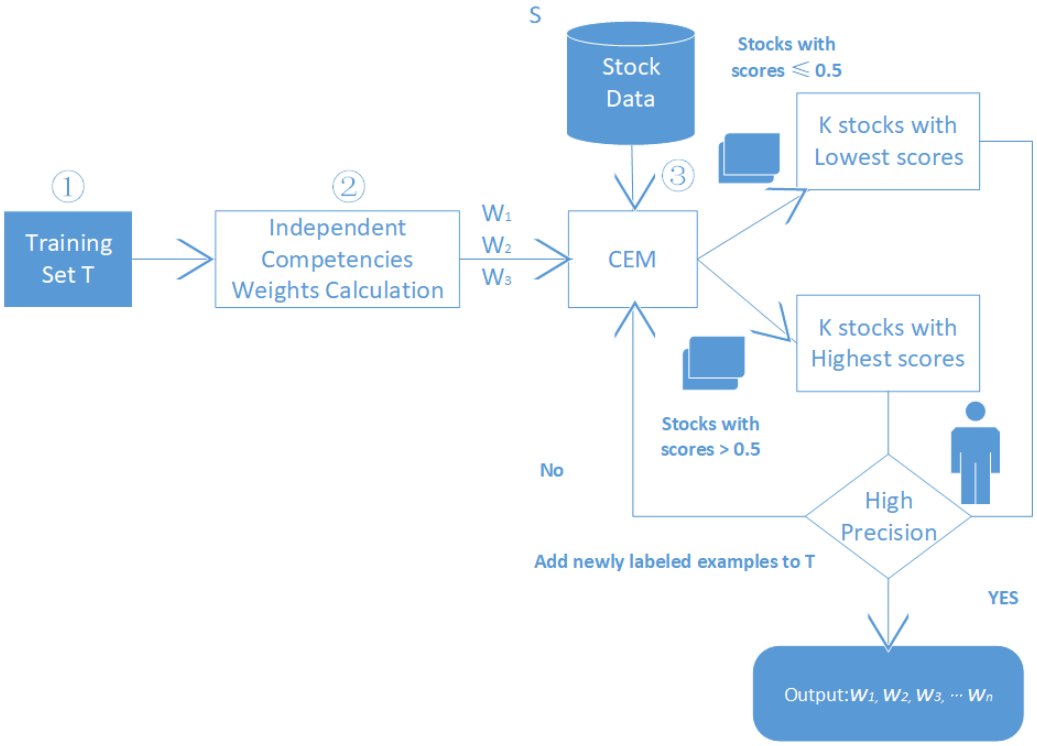

Figure 7. Active learning process in construction of CEM.

Our goal is to obtain a generalized linear function Figure 6b, with high precision in judging the comprehensive competencies for SMEs. As is illustrated above, CEM combines the weights of AHP(W_1), Entropy(W_2) and CRITIC(W_3) in Formula (11). Here, we used an active learning algorithm to carry out the adjustment work for the factor c_1, c_2, c_3 of these three weights. Firstly, we set the training set T to be empty. We used AHP, Entropy and CRITIC to calculate their independent competitive weight vectors (W_1, W_2, W_3,), and combined the three weights with the same coefficient to obtain the initial CEM ($c_1 = c_2 = c_3 = \frac{1}{3}$). Next, we input each index value of SME into CEM. Here, the threshold of *competency* is set to 0.5, k stocks with the highest comprehensive competitiveness score H_x and k stocks with the lowest comprehensive competitiveness scores are taken respectively, which are judged by domain experts. If a stock is judged as "low competitiveness" by CEM while actually behaves "highly competitive", then the record is marked as an erroneous judgment. Conversely, it is a correct judgment. When the accuracy of the judgment is higher than a certain value (e.g., 0.8), which means that the current round meets the accuracy rate greater than the value. This indicates that the model has a good training effect and the model in this round will be output as final CEM. Otherwise, the marked data will be input into the training set T, and the coefficients of each weight in the model are adjusted through active learning again. A more systematic algorithm description is shown below in Algorithm 1:

Algorithm 1 Framework of Active Learning for Coefficients of AHP Weight, Entropy Weight and CRITIC Weight.

Input: The initial coefficient for AHP weight, W_1; The initial coefficient for Entropy weight, W_2; The initial coefficient for CRITIC weight, W_3; Threshold for judgment precision, $Threshold_p$; Number of records selected for human judgment, k; Stock data set, SD; CEM function, $CEM(x)$; Learning module function $LM(x)$;

Output: The initial coefficient for AHP weight, W_1; The initial coefficient for Entropy weight, W_2; The initial coefficient for CRITIC weight, W_3;

Training Set $T \leftarrow empty$;
for company $c_i \in SD$ **do**
    $score_{stock_i} = CEM(c_i)$
end for
$score_{stock} \leftarrow$ sorting companies according to $score_{stock}$;
for stock $s_i \in k$ companies with highest scores and k companies with lowest scores **do**
    if companies in c_i is with high competency **then**
        $score_{stock_i} = 1$;
    else
        $score_{stock_i} = 0$;
    end if
    Put c_i into T;
end for
Precision $\leftarrow$ calculating precision of $score_{stock_i}$
if Precision $> Threshold_p$ **then**
    return W_1,W_2,W_3;
else
    W_1,W_2,W_3 = $LM(T)$
    repeat Step 5 to Step 15
    until Precision $> Threshold_p$
    return W_1,W_2,W_3;
end if

Here, we use the accuracy rate (the ratio of the CEM decision result to the actual situation), the recall rate (the ratio of the highly competitive SME in reality is determined by the CEM to be highly competitive) and the error rate. The comparison results show that CEM is better than the three independent methods in Accuracy (0.82) and Recall (0.85). At the same time, the CEM algorithm proposed in this paper has the lowest error rate, as is revealed in Figure 8.

We also compared the time complexity of different competitiveness evaluation algorithms, as shown in Table 8. The value k is the number of samples extracted from extreme values during each round of active learning, which is much less than the number of samples n. From Table 8, it can be found that CEM has the best time complexity.

Table 8. Comparison of the time complexity of different competency evaluation algorithms.

-	AHP	Entropy	CRITIC	CEM
Time Complexity	$O(n^2)$	$O(nlog_2n)$	$O(n^2)$	$O(klog_2n)$

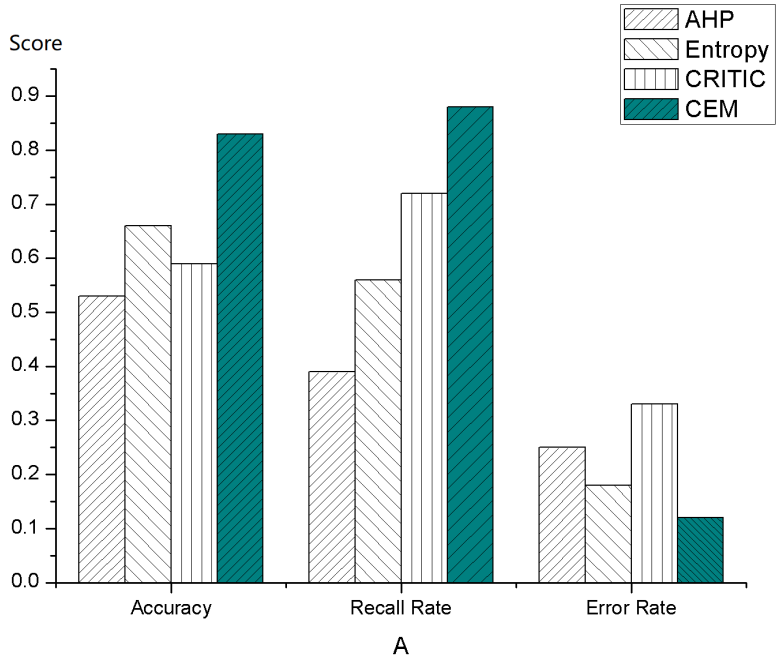

Figure 8. Performance comparison of different competency evaluation algorithms.

4. Results

4.1. The Number of SMEs and the Number of Listed SMEs Have Continued to Grow for Three Years

Statistics show that the total number of SMEs registered in NEEQ increased from 12,000 in 2015 to 32,000 in 2017, and the total number of SMEs in the Chinese market increased by 1.6 times in three years. At the same time, the number of newly listed SME stocks in SSE and SZSE also increased from 1310 in 2015 to 13,395 in 2017, as shown in Figure 9. Among them, the growth trends of SMEs' total amount becomes flat, while the newly listed SME stocks are still increasing at a rapid rate.

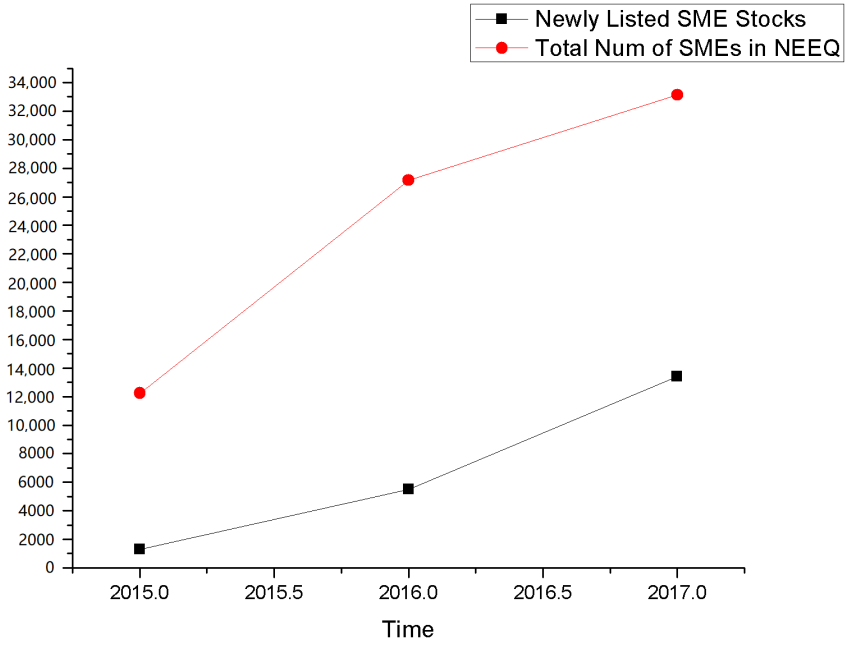

Figure 9. SMEs and newly-listed SME Stocks in the China Market, 2015–2017.

The continuous increase in the number of SMEs shows that the SME itself is developing rapidly and the future is more optimistic. At the same time, through the following Figure 10, the proportion of SMEs in the China stock market (SSE and SZSE) is nearly 42%, accounting for the largest share in China's stock market. We can assume that the core competencies of SMEs is also representative of the current Chinese market.

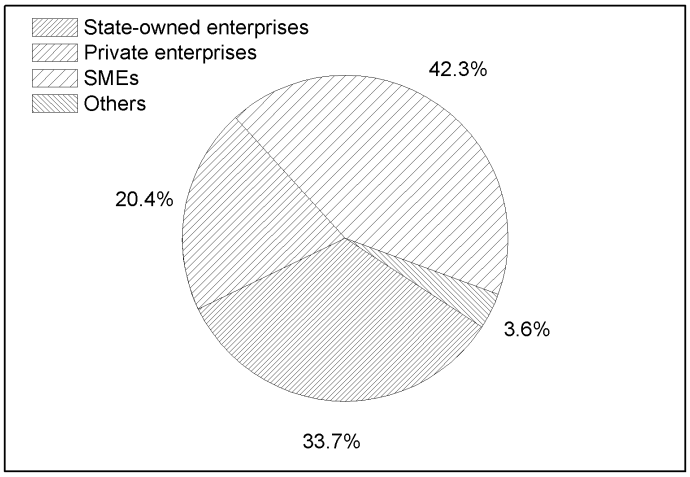

Figure 10. The proportion of various types of stocks in SSE and SZSE.

4.2. The Most Popular Business Scopes Are Manufactory Industry and Information Technology

Among the 3430 SMEs from Chinese stock markets (SSE and SZSE) studied in this paper, 64.02% of the companies are classified in the manufacturing industry, and 27% are in the information technology (IT) industry. The specific distribution is shown in Figure 11. This phenomenon is quite different from other markets. In the US stock market, the scope of the information technology industry is even larger. In the Chinese market, SMEs involved in the information industry often choose to be merged by larger IT companies (such as Tencent) instead of listing themselves.

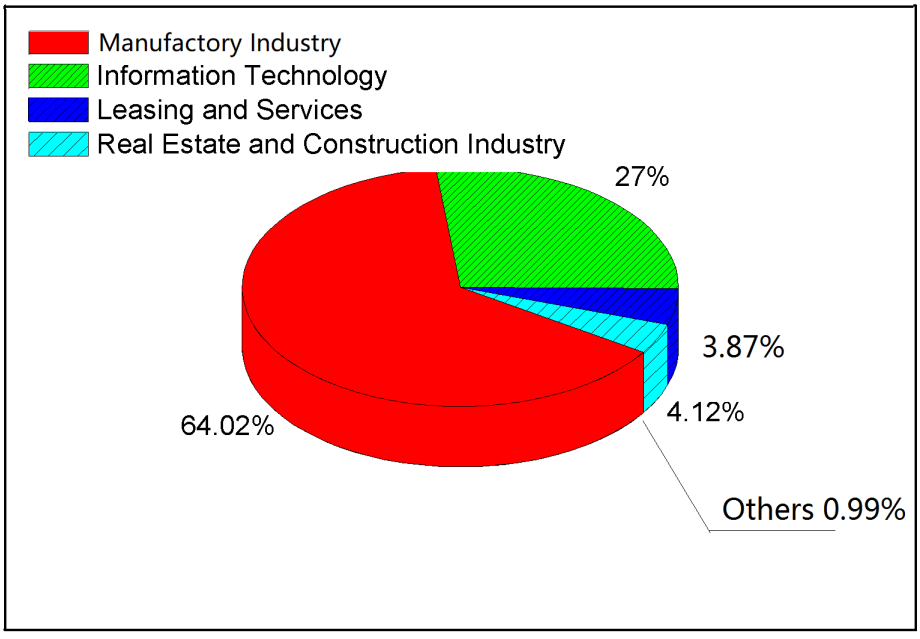

Figure 11. Distribution of researched companies' business scopes.

It is worth noting that the main business scope of the current SME is still the manufacturing and IT industries. For enterprises, more attention can be paid to these two business scopes, and even a combination of two business scopes can be considered to some extent. For investors, choosing a manufacturing-backed SME to invest is a wise choice.

4.3. Most of Newly-Listed SMEs Are from Jiangsu, Beijing and Shanghai

In the experiment, we also found that in the 3430 SMEs surveyed, 33.3% came from Jiangsu, 20% came from Beijing, 13.3 came from Shanghai, and 6.7% came from Guangdong, as is shown in Figure 12.

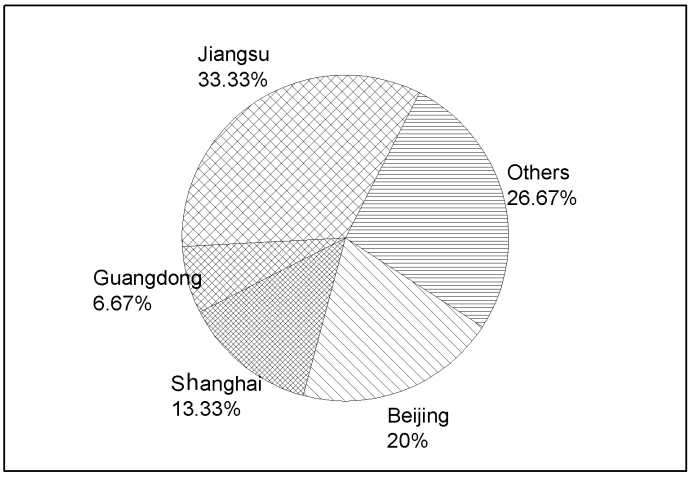

Figure 12. Distribution of locations of newly-listed SMEs.

This phenomenon coincides with the previous conclusions about the business scopes of the SMEs. In the Chinese market, manufacturing enterprises are mainly located in Jiangsu, while Beijing, Shanghai and Guangdong are the main gathering places for information technology companies. Geographical distribution also reflects the main distribution of business scope in the current market environment. As a business operator, if the main business scope of enterprise is manufacturing industry, it is suggested to consider setting up a company in Jiangsu. If the main scope of business is information technology, the location of the business in Beijing, Shanghai, or Guangdong is the recommended setting.

4.4. Number of Stock Market Makers, Equity Financing Frequency and Executive Replacement Frequency Are Three Main Core Competencies

The figure below (Figure 13) shows the weight of each competency indicator in CEM after active learning in 45 secondary indicators. The final CEM we obtained is as Formula (12), where x_i represents the specific value of the secondary competency indicator and w_i is the weighting factor of the corresponding indicator in the final *competency*:

$$Competency = w_1x_1 + w_2x_2 + \cdots + w_{45}x_{45}. \quad (12)$$

Here, we remove some of the competencies that are too low in weights (less than 0.001 in CEM), leaving the remaining 31 competencies. Among them, Number of Stock Market Makers (ID: 17, weight: 0.360), Equity Financing Frequency (ID: 24, weight: 0.085) and Executive Replacement Frequency (ID: 14, weight: 0.063) are the three highest-priority core competencies. Table 9 shows the specific weights for the listed 31 competencies in Figure 13.

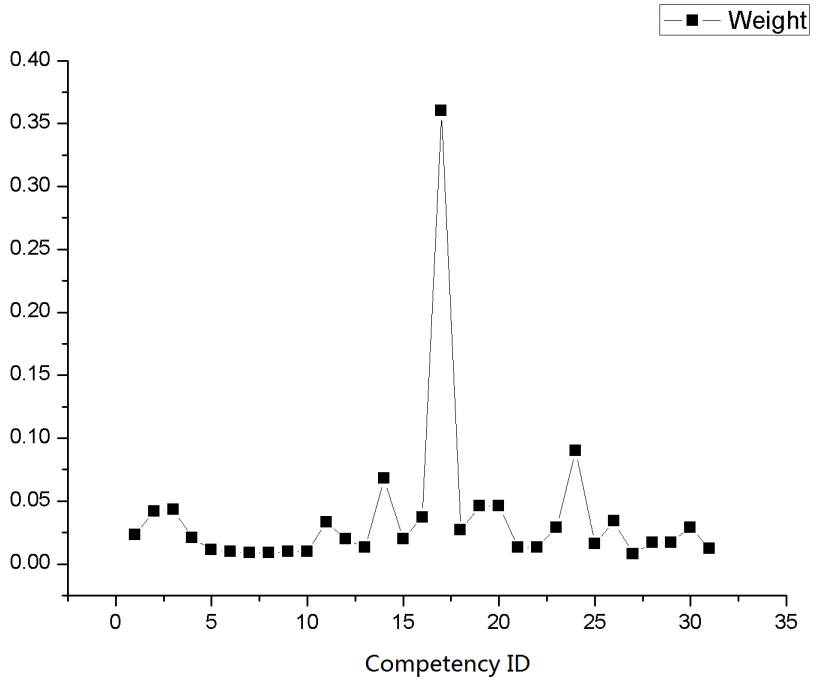

Figure 13. Weights of different competencies of SMEs (2015–2017).

Table 9. Specific weights in CEM for core competencies.

Competency ID	Competency Name	Weight in CEM
1	Operating Income	0.023
2	Average Growth Rate of Net Profit	0.045
3	Main Business Growth Rate	0.047
4	Return of Net Assets	0.021
5	Total Assets	0.013
6	Total Asset Turnover	0.011
7	Number of Users Market Share	0.010
8	Number of Shareholders	0.010
9	Total Financing Amount	0.013
10	Junior College Ratio	0.012
11	News Media Attention Index	0.029
12	WeChat Attention Index	0.024
13	Regional Level of the Company's Area	0.021
14	Executive Replacement Frequency	0.063
15	Computer Copyright Quantity	0.024
16	Total Number of Trademarks	0.026
17	Number of Stock Market Makers	0.360
18	Webmaster Ranking	0.023
19	Number of Executive Replacements	0.044
20	Bond Financing Amount	0.044
21	Popularity of Industry	0.020
22	Percentage of R&D Investment to Operating Revenue	0.019
23	Number of Subsidiaries	0.025
24	Equity Financing Frequency	0.085
25	Total Number of Certificates	0.019
26	Media Attention Index	0.026
27	Baidu Records	0.008
28	User Market Share	0.015
29	Three-year Main Business Compound Growth Rate	0.015
30	Three-year Net Profit Compound Growth Rate	0.024
31	Three-year Total Assets Compound Growth Rate	0.012

The table and figure show that Number of Stock Market Makers is the core competitiveness of the SME, and its weight in the CEM is the highest. Competencies with weights over 0.04 are: Average growth rate of net profit, Main business growth rate, Executive Replacement Frequency, Number of Market Makers, Number of executive replacements, Bond financing amount and Equity Financing Frequency.

4.5. About 60% of Companies Invest More Than 5% of Total Revenue in the Technology Business

As shown in Figure 14, out of the 3430 SMEs, 57% of SMEs invest more than 5% in the IT business, while SMEs that invest more than 2% in the IT business reach 90%. However, according to Table 10, the researched SMEs actually have a variety of main business scopes. This phenomenon is to some extent consistent with the current trend of the WEB 2.0 era. Regardless of the type of main business, SME will have a certain investment in the IT field.

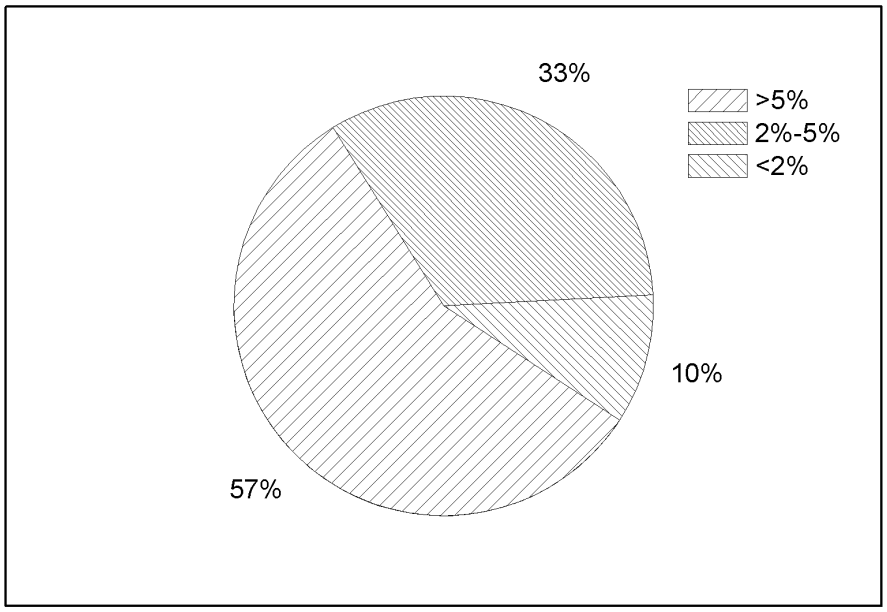

Figure 14. Distribution of the investment percentage of the IT business for SMEs.

Table 10. Distribution of main business scopes of 3430 listed SMEs in SSE and SZSE.

Main Business Scope	Total
Manufacturing	2195
Information Technology	926
Leasing and Service	133
Real Estate and Construction	141
Others	35

5. Discussion

5.1. What Kinds of Competencies Show a Strong Influence in the Current Chinese Market?

From the results of the CEM output (Figure 13 and Table 9), the number of market makers is the most important core competency for an SME. Market makers hold stocks of certain SMEs, and as such undertake to maintain the two-way trading of these SMEs. Therefore, the more market makers are, the more SMEs show their competitiveness in the stock market through maintaining a satisfactory stock price.

It is worth noting that financial factors play an important role in the core competencies of SMEs. The number of market makers, the frequency of equity financing, the average growth rate of net profit, the growth rate of main business, and bond financing amount occupy five out of seven positions in the core competencies with weights more than 0.04. In the current Chinese market, especially for SMEs, its core competitiveness is financially reflected in the participation of enough market makers, high-frequency financing support, and continuous growth of its own business and profits.

At the same time, we should not neglect non-financial factors which also have two core competencies whose weights over 0.04, executive replacements' times and executive replacement frequency. In fact, these two core competencies measure the stability of SMEs. We know that the replacement of excessively high frequency, excessively large numbers of directors or senior managers will cause the SME's own development strategy to fluctuate, which is not conducive to the development of the SME itself. On the other hand, because SMEs are not very large in terms of their own capital, it is difficult to assume the risk of strategic decision-making like large companies. Therefore, a stable decision-making layer is an important competitive factor among non-financial competencies.

5.2. What Business Scopes Show a Promising Development Trend?

Before conducting the experiment, domain experts originally predicted that IT and finance would occupy a large proportion of SMEs in China. However, in reality, the largest proportion of the existing Chinese SME market is manufacturing. This shows that, in the Chinese market, competitive SMEs still need strong products as support.

However, it is undeniable that the SMEs that mainly run IT businesses account for the second highest proportion in the current Chinese market. This phenomenon shows that, in the WEB 2.0 era, the IT industry played a significant role in promoting the newly listed SMEs' development.

Based on the above findings, we believe that, in the existing Chinese market, an SME with genuine manufacturing or product support will be highly competitive, having broad prospects. At the same time, the three industries—IT, finance and real estate—also have a good future prospect in the current Chinese market. Naturally, if an SME can combine IT and manufacturing in a smooth way or integrate IT technology into its main business, it will be more competitive than existing SMEs.

5.3. What Kinds of SMEs Are in Alignment with the Recent China Market Trend?

Based on the above data and findings, we have summarized several special features of SMEs that are consistent with the current development trend of the Chinese market from the following perspectives.The SME with one or more of the following features deserves the attention of investors. At the same time, for SME operators, they also need to pay attention to whether their own companies meet the following requirements.

Good Performance in CEM Core Competencies. In terms of financial competencies, SMEs need to have good performance on net profit margin, business growth rate, and bond financing amount, which is a basic condition. At the same time, the company also needs a stable management team to ensure the consistency of the business and the stability of the strategy.

Consistent with the Local Development Strategy. As is revealed in Figure 12, at present, the largest number of SMEs in the Chinese market do not come from a large-scale. The traditional urban clusters such as Beijing, Shanghai, and Guangdong, on the contrary, come from Jiangsu, which has very good support for manufacturing. This phenomenon calls for the attention of business operators and investors that the consistency in the location of the company with local policies is more important than the local economic development state itself.

Combination of Core Products and IT Technologies. In the current Chinese market, an SME with a core product still has a strong competitive edge. However, we recommend adding some cutting-edge IT technologies to the core product during the process of establishing and promoting. This will make SMEs more differentiated and thus more competitive in the market.

6. Conclusions

Indeed, the core competencies definition has changed and continues evolving with the development of information technology (IT). In the meantime, the development itself brought a total reformation in business operation, the unique characteristics, and the policies of the Chinese market, which could be discovered from the evolution of core competencies. We demonstrated an active learning based algorithm to carry out the construction of CEM, which could give reasonable weights to the competencies of the company. We stressed that Xiaofeng's standard for the business core competencies definition method may need improvements. With periodic review and maintenance, the document may evolve with the profession and remain relevant, which is beneficial to those who seek guidance.

The adequate data with high accuracy surely produces more comprehensive and accurate evaluations. All the data are retrieved from the SSE and SZSE stock price series and the annual report data from NEEQ, the official finance news-websites for business research in China. There are still about 22% of the data that have only simple and shallow core competencies-related descriptions that made construction of final CEM difficult and cannot be extended with other data mining methods. At the same time, the active learning method adjusted the result of individually applying subjective evaluation methods (e.g., AHP) or objective evaluation methods (e.g., Entropy, CRITIC), which made a great improvement on final performance. CEM is based on previous work and manually updated it to ensure its effectiveness. On the other hand, because this method provides researchers with limited candidates in the human marker portion, a large number of market core competency weights can be processed.

Since this study uses active learning methods to set the weights of each core competency, and uses a semi-automated approach to build CEMs based on previous evaluation models, it is easy to apply this method to samples from the same source. Researchers can track changes in the core competencies of the Chinese market through repeated surveys. Another possible improvement on this study is the inclusion of supplemental data from other sources, which may be a good complement. In addition, the date of the annual report in this study ranges from 2015 to 2017. The annual report of the company released before 2015 can be in sharp contrast to the trend of analyzing the core competitiveness of the business.

The algorithms presented in this article can also be applied in the following areas:

(1) Combining multiple evaluation models to obtain a scenario for a comprehensive evaluation model. For example, when an individual personal consumption situation assessment model and an individual loan habit evaluation model are required to obtain an individual's comprehensive economic ability assessment model, the active learning algorithm in this article can be used. At the same time, for the model in this paper, we can also add other external factors (such as news, microblogging, etc.) to improve the CEM performance.

(2) The performance data of the core competencies in this article comes from the annual report in NEEQ. In fact, the core competitiveness performance of the companies will be reflected in the daily news, Weibo or WeChat posts. Through these channels, we can obtain more accurate core competencies' scores in the future.

Last but not least, the authors demonstrated a CEM that combines AHP, Entropy and CRITIC. Only a little of the human tagging work could lead to a satisfactory weights assigning result. Further work will introduce other evaluation models into the CEM to create more useful classification work.

Author Contributions: X.D. directed the research; L.D. reviewed related literature and confirmed the research topic; L.D. designed and implemented the algorithm under X.D. guidance, performed the experiment, analyzed the data and wrote the paper with discussions and contributions from all the authors; L.D. contributed the data source, manually analyzed the business scopes and edited the paper.

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